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Soil Recycling Among Construction Sites by Optimizing Schedule and Costs for Earthmoving

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Abstract

Recycling uncontaminated excavated construction soil is beneficial because it reduces the costs to abandon excess soil or obtain refill soil from a distant location while alleviating environmental burdens. For this reason, various methods and techniques to support on-site soil reuse have been explored. However, in order to increase the reuse rate, excavated soil should be recycled among different construction sites as well. As a prerequisite for reusing excess soil in this context, the construction schedules, type of soil, trading volume, and incurred costs must be coordinated. In order to consider all of these aspects, earthmoving among construction sites needs to be planned by means of multi-objective optimization. This paper aims to present a practical solution supporting inter-site soil trade by introducing a non-dominated sorting algorithm-II (NSGA-II), a type of multi-objective evolutionary algorithm (MOEA). A description of the optimization procedure is provided, and computational results are presented to prove the effectiveness of the selected method.

Keywords: excavated soil; solid waste management; multi-objective evolutionary algorithm; non-dominated sorting algorithm-II

1. Introduction

Soil is a non-renewable and limited natural resource. Nevertheless, in the construction industry, the recycle rate of excavated soil is assumed to be low (Blengini and Garbarino, 2010). When the volumes between excavated and refill soils are unbalanced, the remnant soil should be processed outside of the site. In the worst cases, excavated soils are treated as waste (Johansson *et al.*, 2013). At the societal level, excavated soil reuse can reduce the environmental burden associated with obtaining natural fresh soil and decrease CO₂ emissions by reducing transportation to disposal sites and quarries (Magnusson *et al.*, 2015). From a financial perspective, soil movement is a significant part of construction costs, representing between 5% and 16% of the capital cost of infrastructure projects (Manahan, 2012).

An ideal scenario is to reuse the excavated soil by selling or transferring it to other construction sites that require it. However, such a situation is only realized when the schedules of the respective sites are properly

coordinated and economic benefits are provided to all parties, both cut and fill sites. As a practical solution, Earth Information Systems (EISs) have been developed to provide information on soil availability, needs and tracking. South Korea transacts soil and rock via an open portal, TOCYCLE (Moon *et al.*, 2007), and a similar system, Fill Sites, is operating in Australia. Ontario, Canada is launching a Best Practice Management Program to enhance the soil reuse rate (RCCAO, 2012) and implements SoIIL, a soil "matching system" website.

Even with currently available information systems, a few challenges still exist that hinder soil transactions among construction sites. For example, the seller and buyer are likely to conceive different trade volumes and costs for a given transaction. Dissimilar conditions associated with the respective construction sites also require that certain arrangements should be made for particular earthmoving operations. Moreover, manual planning of trades while optimizing schedules and costs is an exhausting task for responsible field managers.

All conditions and requirements should be met in order to facilitate soil recycling among sites and thus the optimization in this context is a multi-objective problem. This challenge is common in solid waste management and various methods have been introduced to present solutions. For instance, Mavrotas *et al.* (2013) introduced multi-objective mathematical programming

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into optimal solutions to reduce Greenhouse Gas (GHG) emissions while considering cost effectiveness in the context of Municipal Solid Waste (MSW) management. Swapn and Bhattacharyya (2015) used the Travelling Salesman Problem (TSP) to optimize collection schedules and routes.

However, in construction academia, excavated soil recycling among sites has attracted less attention. Instead, methods to optimize earthmoving operations on-site have been developed. An integrated simulation-genetic algorithm (GA) for optimizing earthmoving operations was implemented by Marzouk and Moselhi (2004). They executed experiments on diverse fleet configurations and minimized exhaustive computational operations. Reflecting the multiple criteria of time and cost, Zhang (2008) utilized a simulation-based optimization method implemented by following the swarm mechanism for configuring earthmoving fleets. Lin *et al.* (2012) integrated a discrete event simulation technique and GA to optimize truck configuration. Considering influential factors in earthmoving optimization, Cheng *et al.* (2011) employed Petri net simulations in order to provide earthworks managers with optimal situations, equipment utilization rates, and estimated durations/costs. While the aforementioned studies and many other related papers have focused on single-site earthmoving operations, Chu *et al.* (2012) addressed inter-site earthmoving by applying multiple time-space networks for soil recycling and truck dispatching while taking earthmoving schedules into account. Previous research is largely useful for field managers who organize vehicles for earthmoving in a single site. However, simulation of practical applications is still required to plan inter-site soil trade. Since factors of excavated soil trade or transfer such as volume of soil, costs, and schedules are interdependent, a meta-heuristic method is required to solve the multi-objective problem.

This paper presents a practical application to support inter-site earthmoving optimization while coping with the multi-objective problem by introducing solutions that have gained popularity in the field of solid waste management (Mavrotas *et al.*, 2013). The non-dominated sorting genetic algorithm-II (NSGA-II) is introduced, as it performs well in terms of generating and sorting populations of solutions compared to other multi-objective algorithms (Watanabe *et al.*, 2000). Specifically, Deb *et al.* (2000) showed that NSGA-II can create optimal trade-offs of multiple objectives in a single attempt. Furthermore, NSGA-II utilizes an elitist strategy, which averts the loss of optimal solutions resulting from the former optimization strategies. In this paper, the main role of NSGA-II is to solve two conflicting objectives: minimizing earthmoving costs associated with cut and fill sites while simultaneously satisfying construction schedules. The formulated problems and optimized results are presented, along with a description of NSGA-II.

2. Mathematical Formulation of Excess Construction Soil Trade

2.1 EIS in Use and Problem Statement

Various information systems have been developed to support soil recycling in the field of inter-site earthmoving. As a single instance out of many, TOCYCLE is designed to facilitate real-time information sharing on soil excavation and transport and fill volumes among construction sites. A screenshot of TOCYCLE in operation is presented in Fig.1. The fundamental concept of this system is similar to the GIS-based optimized solid waste collection system (Kanchanabhan *et al.*, 2011; Rada *et al.*, 2013). The information presented in the system includes the physical location of the site, the soil types, the scheduled amount of excavation or fill, and options for the mitigation of additional costs. Analysis of the

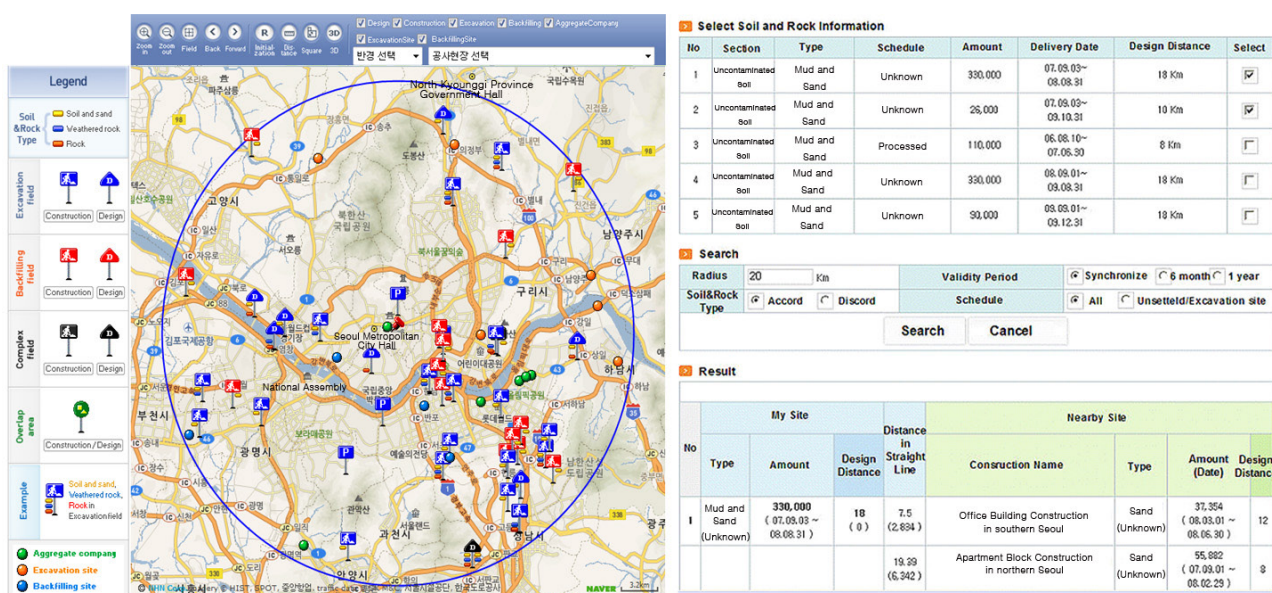


Fig.1. A Screen Shot of TOCYCLE

operation of TOCYCLE over the three-year period of 2005 to 2007 revealed an average savings of about 4.4% in earthworks cost (Moon *et al.*, 2007).

When establishing plans for earthmoving among sites, the timing, trading parties, volume of soils, and the cost for each side should be accounted for, and either the total cost or any type of loss must be minimized. However, in a construction sites group (CSG) comprised of cut and fill sites, minimizing the cost of any one site may not, in most cases, minimize the total cost of the CSG as a whole. In other words, if a cut site costs less, then that much of cost reduction is converted into a burden to the fill site since one side's gain means the other side's loss in a usual transaction. Furthermore, coordinating the schedules of sites can be rather challenging, as it has a direct impact on the construction operation and costs. Such problems serve to complicate soil transactions.

As an example for optimization, surplus and required volumes of soil in a group of construction sites are provided, along with earthmoving schedules in Fig.2. First, the cost associated with a cut site should be considered. One of the major cost components for a cut site is the hauling cost, which depends on both the travel distance and the amount of soil transported. In order to reduce the total earthmoving cost to transport soil from a cut site to a fill site or designated disposal area, two options are available as follows: (1) reducing the share of inter-site earthmoving costs that the cut site is willing to accept, or (2) altering the earthmoving schedule of all sites in a CSG so as to increase the

volume transported and to decrease the haul distance between the cut site and fill site as far as the scheduling flexibility (or total floats) allows.

The immediate effect of the first option is to increase the soil procurement cost for the fill site, because it should purchase soils rather than sharing soil with cut sites. If the inter-site earthmoving cost, which includes selling and purchasing surplus soils between construction sites, is less than that of utilizing a borrow pit and disposal area, it is, at first glance, rational to commence inter-site earthmoving between the respective sites. However, the effect of cost minimization for a CSG depends on the share of costs that both sites are willing to accept. For instance, there are two possible scenarios where the share of inter-site earthmoving costs borne by the fill site is greater than that of the cut site and the procurement cost from the borrow pit. If a deal is concluded, the cost for utilizing the pit decreases but the inter-site earthmoving cost increases. On the other hand, if a deal is not made, the fill site can pay the cost for the borrow pit. In addition, surplus soil that is not transported to a nearby fill site may be delivered to distant fill sites or charged-disposal areas, thereby impeding efforts to minimize the total earthmoving cost of a CSG.

The effect of the second option is to increase the potential volume of soils procured from the borrow pit. Since a construction site is willing to make a deal with sites when the inter-site earthmoving cost that one party can accept is less than or equal to the cost of utilizing remote sites (e.g., a disposal area or borrow pit), the total earthmoving cost of a CSG may be increased. In

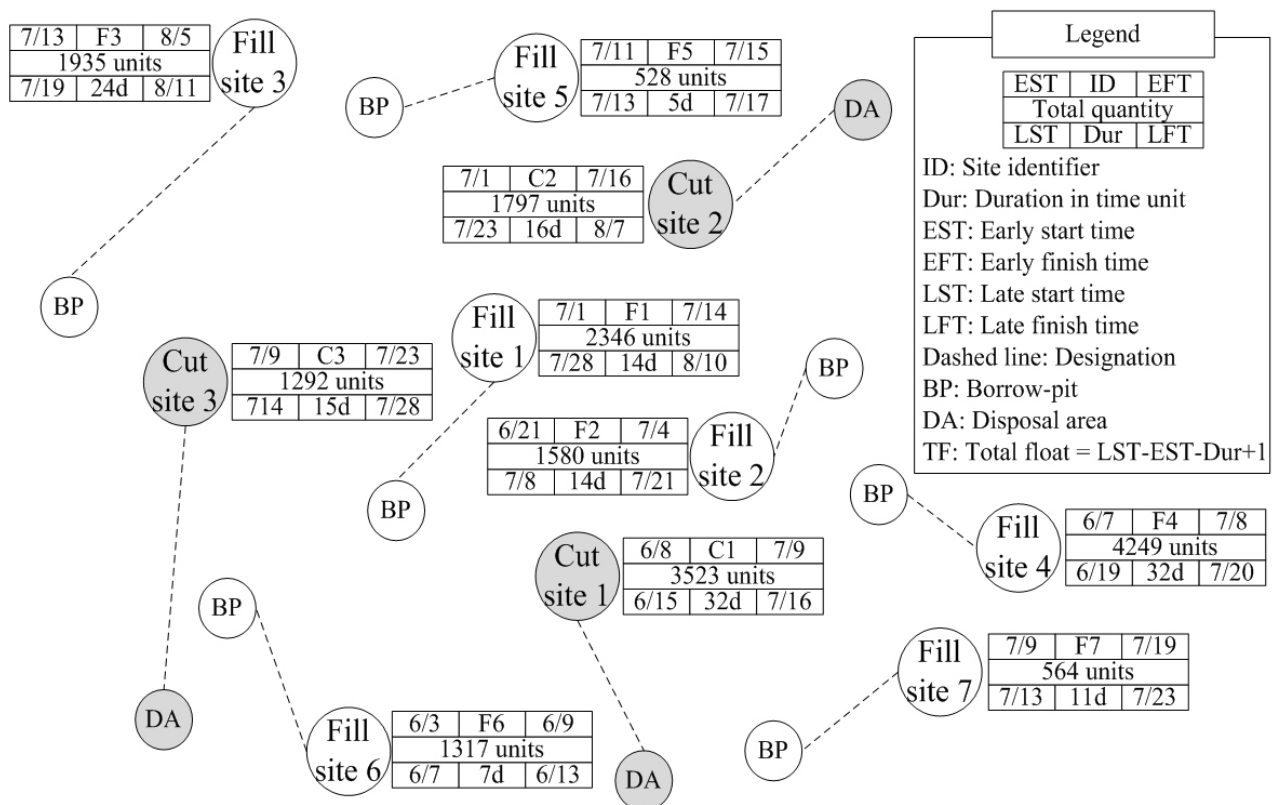


Fig.2. Earthmoving Schedules of a Construction Sites Group

Table 1. Decision Variables and Parameters

Decision variables		Parameters	
Variables	Descriptions	Variables	Descriptions
X_j^i	$\begin{cases} 1, \text{if cut site } j \text{ exists} \\ 0, \text{otherwise} \end{cases}$	T_{CFjk}^i	Unit transportation cost of soil i for transporting soil from cut site j to fill site k at time t
Y_k^i	$\begin{cases} 1, \text{if fill site } k \text{ exists} \\ 0, \text{otherwise} \end{cases}$	T_{CDjd}^i	Unit transportation cost of soil i for transporting soil from borrow pit designated for fill site k to fill site k at time t
Z_{jk}^i	$\begin{cases} 1, \text{if earthmoving between cut site } j \text{ a} \\ 0, \text{otherwise} \end{cases}$	T_{FBkb}^i	Unit transportation cost of soil i for transporting soil from cut site j to fill site k at time t
U_{CFjk}^i	Units of soil i transported from cut site j to fill site k at time t	EL_{Cj}^i	Unit excavation and loading cost of soil i for excavating and loading soil at cut site j at time t
R_{Cj}^i	Units of remaining surplus soil i at cut site j at time t	EL_{Bkb}^i	Unit excavation and loading cost of soil i for excavating and loading soil at borrow pit designated for fill site k at time t
R_{Fk}^i	Units of remaining deficient soil i at fill site k at time t	PC_{Djd}^i	Unit placement and compaction cost of soil i for placing and compacting soil at disposal area designated for cut site j at time t
D_{Cj}^i	The total number of work periods required to accomplish excavation of soil i at cut site j	PC_{Fk}^i	Unit placement and compaction cost of soil i for placing and compacting soil at fill site k at time t
D_{Fk}^i	The total number of work periods required to accomplish backfilling of soil i at fill site k	SU_{Cj}^i	Setup cost of disposal area designated for cut site j for soil i
L_{CFjk}	Distance between cut site j and fill site k	SU_{Fk}^i	Setup cost of borrow pit designated for fill site k for soil i
L_{CDjd}	Distance between cut site j and disposal area designated for cut site j	SR_{Cj}^{iactl}	Actual share of the total inter-site earthmoving cost (sum of hauling, excavation, and landing costs for soil i) that cut site j can accept
L_{FBkb}	Distance between fill site k and borrow pit designated for fill site k	SR_{Fk}^{iactl}	Actual share of the total inter-site earthmoving cost (sum of hauling, excavation, and landing costs for soil i) that fill site k can accept
		I_{Dj}^i	Units of soil i disposed from cut site j to disposal area designated for cut site j at time t
		I_{Bk}^i	Units of soil i procured from designated borrow pit for fill site k to fill site k at time t

particular, an optimization strategy to maximize cut site benefits by increasing the transaction volume and decreasing the haul distance does not always reduce the total earthmoving cost in a CSG. This is because a schedule-oriented optimization for only a single party, whether it is a cut site or fill site, can cause an inefficient distribution or reallocation of the soils. As the total volumes of surplus and deficient soils could be mismatched and the flexibility for scheduling could be limited, a cut site's schedule-oriented optimization leads to an intermittent bottleneck state at the fill sites. Such a scenario indicates that the total earthmoving cost of a CSG cannot be minimized. Therefore, simultaneously decreasing the total earthmoving costs of cut and fill sites is important.

The ultimate goal of this research is to solve the inter-site earthmoving optimization problem for construction sites where a surplus or deficiency in soils arises. Particular emphasis is given to minimizing the total costs of cut and fill sites so that the total profits gained from a given transaction can be maximized. Accomplishing these particular objectives is quite critical in current earthmoving operations, since each site is able to conduct cost-effective construction by minimizing costs. In Table 1., relevant notations used in this research are provided. The formulated problem is then described in subsequent subsections.

2.2 Notation and Formulated Problem

A formulation of the multi-objective problem will now be provided. For the sake of convenience, the authors consider only four types of costs in this paper: (1) excavation and loading cost, (2) haul cost, (3) placement and compaction cost, and (4) setup cost for remote sites.

Objective 1 described in Equation (1) is to minimize the total cost of cut sites, which can be divided into the following items: (i) the excavation and loading cost for inter-site earthmoving that cut sites can accept, (ii) the transportation cost for inter-site earthmoving that cut sites can accept, (iii) the placement and compaction cost incurred at the disposal area, (iv) the transportation cost incurred from hauling soil from cut sites to each designated disposal area, and (v) the setup cost for the disposal area.

$$\text{Minimize } Z_1 = \sum_{i=1}^P \sum_{j=1}^W \sum_{k=1}^D U_{CFjk}^i SR_{Cj}^{iactl} EL_{Cj}^i X_j^i Y_k^i Z_{jk}^i + \sum_{i=1}^P \sum_{j=1}^W \sum_{k=1}^D U_{CFjk}^i SR_{Cj}^{iactl} T_{CFjk}^i L_{CFjk}^i X_j^i Y_k^i Z_{jk}^i + \sum_{i=1}^P \sum_{j=1}^W I_{Dj}^i PC_{Djd}^i X_j^i + \sum_{i=1}^P \sum_{j=1}^W I_{Dj}^i T_{CDjd}^i L_{CDjd}^i X_j^i + \sum_{i=1}^P \sum_{j=1}^W I_{Dj}^i SU_{Cj}^i X_j^i \quad (1)$$

$$\text{Minimize } Z_2 = \sum_{i=1}^P \sum_{j=1}^W \sum_{k=1}^D U_{CFjk}^i SR_{Fk}^{iactl} PC_{Fk}^i X_j^i Y_k^i Z_{jk}^i + \sum_{i=1}^P \sum_{j=1}^W \sum_{k=1}^D U_{CFjk}^i SR_{Fk}^{iactl} T_{CFjk}^i L_{CFjk}^i X_j^i Y_k^i Z_{jk}^i + \sum_{i=1}^P \sum_{j=1}^W I_{Bk}^i EL_{Bkb}^i Y_k^i + \sum_{i=1}^P \sum_{j=1}^W I_{Bk}^i T_{FBkb}^i L_{FBkb}^i Y_k^i + \sum_{i=1}^P \sum_{j=1}^W I_{Bk}^i SU_{Fk}^i Y_k^i \quad (2)$$

Objective 2 described in Equation (2) is to minimize the total cost of a fill site, which can be divided into the following items: (i) the placement and compacting cost for inter-site earthmoving that the fill sites can accept, (ii) the transportation cost for inter-site earthmoving that the fill sites can accept, (iii) the excavation and loading cost incurred at the borrow pit, (iv) the transportation cost incurred from hauling soil from each designated borrow pit to fill sites, and (v) the setup cost for the borrow pit.

The constraints of the problem presented in Equations (3) to (10) are as follows. "A unit of soil" can be defined as the amount of soil that an individual vehicle can carry in one trip. Here, $U_{CF_{jk} \min}^i$ and $U_{CF_{jk} \max}^i$ are the minimum units of soil i transported from cut site j to fill site k at time t , and the maximum units of soil i transported from cut site j to fill site k at time t , respectively. Likewise, $SR_{C_j \max}^i$ and $SR_{F_k \max}^i$ denote the maximum share of the total inter-site earthmoving costs (i.e., the sum of hauling, excavation, and landing costs for soil i) that cut site j and fill site k are willing to accept, respectively.

$$I_{D_j^i} = R_{C_j^i} - \sum_{l=1}^P \sum_{k=1}^D U_{CF_{jk}^i} X_j^i Z_{jk}^i \quad (3)$$

$$I_{B_k^i} = R_{F_k^i} - \sum_{l=1}^P \sum_{j=1}^W U_{CF_{jk}^i} Y_k^i Z_{jk}^i \quad (4)$$

Constraint 3 indicates that the difference between remaining surplus soil i and the sum of soils transported from fill sites is equal to the units of soil disposed from cut site j to a disposal area designated for cut site j . Meanwhile, constraint 4 denotes that the difference between the remaining deficient soil i and the sum of soil transported to cut sites is identical to the units of soil procured for fill site k from a borrow pit designated for fill site k .

$$U_{CF_{jk} \min}^i \leq U_{CF_{jk}^i} \leq U_{CF_{jk} \max}^i \quad (5)$$

$$0 \leq SR_{C_j \max}^i \leq SR_{C_j \max}^i < 1 \quad (6)$$

$$0 \leq SR_{F_k \max}^i \leq SR_{F_k \max}^i < 1 \quad (7)$$

Constraint 5 sets the ranges for the soil units transported for a cycle from a cut site to a fill site at time t . Constraint 6 sets the ranges for the actual share and maximum share that the cut site can accept. Constraint 7 sets the ranges for the actual share and maximum share that the fill site can accept.

$$\begin{cases} [SR_{C_j \max}^i + SR_{F_k \max}^i] \geq Z_{jk}^i \\ SR_{C_j \max}^i + SR_{F_k \max}^i = Z_{jk}^i \end{cases} \quad (8)$$

Constraint 8 denotes the prerequisite for making an inter-site earthmoving deal. If the sum of the maximum shares of both the cut site and fill site is initially less than 1, then Z_{jk}^i is less than or equal to 0, which means

that both Z_{jk}^i and $U_{CF_{jk}^i}$ become 0 (where $[\]$ signifies Gaussian notation). In contrast, if the sum of the maximum shares is greater than or equal to 1, then Z_{jk}^i is less than or equal to 1, and the sum of the actual shares is equal to the value of Z_{jk}^i .

$$\begin{aligned} \sum_{i=1}^P SR_{C_j \max}^i EL_{C_j^i} X_j^i Y_k^i + \sum_{i=1}^P SR_{C_j \max}^i T_{CF_{jk}^i} L_{CF_{jk}^i} X_j^i Y_k^i \\ \leq \sum_{i=1}^P PC_{D_{jd}^i} X_j^i Z_{jk}^i + \sum_{i=1}^P T_{CD_{jd}^i} L_{CD_{jd}^i} X_j^i Z_{jk}^i \\ + \sum_{i=1}^P SU_{C_j^i} X_j^i Z_{jk}^i \quad (9) \end{aligned}$$

$$\begin{aligned} \sum_{i=1}^P SR_{F_k \max}^i PC_{F_k^i} X_j^i Y_k^i + \sum_{i=1}^P SR_{F_k \max}^i T_{CF_{jk}^i} L_{CF_{jk}^i} X_j^i Y_k^i \\ \leq \sum_{i=1}^P EL_{B_{kb}^i} Y_k^i Z_{jk}^i + \sum_{i=1}^P T_{FB_{kb}^i} L_{FB_{kb}^i} Y_k^i Z_{jk}^i \\ + \sum_{i=1}^P SU_{F_k^i} Y_k^i Z_{jk}^i \quad (10) \end{aligned}$$

Constraint 9 means that a cut site is willing to make a deal (i.e., $Z_{jk}^i = 1$) with only the fill site, where the unit cost for earthmoving that the cut site can accept is less than or equal to the cost of utilizing the disposal area.

Lastly, constraint 10 represents a condition in which a fill site is willing to make a deal with only the cut site, where the unit cost of earthmoving that the fill site can accept is less than or equal to the cost of utilizing the borrow pit.

3. Multi-Objective Evolutionary Algorithm

In previous research, the fundamental motivation for adopting the MOEA algorithm was to manage the complexity of the multi-objective optimization problem and leverage the population-based nature of the evolutionary algorithm. In a multi-objective optimization problem, a vector of objective functions is optimized by a vector of decision variables. Due to the presence of multiple objectives, a set of optimal solutions, rather than a single optimal solution, is obtained. The optimization problem requires that the decision maker choose the value of decision variables (Coello *et al.*, 2007) either before or after the search procedure is completed.

3.1 NSGA II

Several MOEA algorithms have been described and utilized in various literatures. Among them, the authors chose to use NSGA-II (Coello *et al.*, 2007) due to its superiority over other MOEA algorithms. The process by which the NSGA-II algorithm is applied to the problem needs to be explained.

The population process is initialized as an ordinary genetic algorithm. Once initialized, the population is sorted into each front according to non-domination. The first front is a completely non-dominant set in the current population, while the second front is dominated

by individuals in the first front only, and this process is successively applied to new fronts. Each individual in the front is assigned rank (or fitness) values, or classified based on the front to which they belong. Individuals belonging to the first front are assigned a fitness value of 1, individuals in the second front are given a fitness value of 2, and so on. The crowding distance, a measure of how close an individual is to its neighbors, is calculated for each individual. A larger average crowding distance signifies better diversity in the population. Through the use of binary tournament selection, parents are chosen from the population according to rank and crowding distance. An individual is selected if its rank is lower than that of others or its crowding distance is greater than that of other individuals. The selected population generates offspring from crossover and mutation operators. The population with the current population and offspring is sorted again according to non-domination, and only the best N individuals, where N is the population size, are selected. Selection is based first on rank and then on the crowding distance in the last front. The measure of the crowding distance is described in the following section.

3.2 Modules of NSGA II

3.2.1 Chromosomes

All variables are represented by a chromosome. Consequently, the number of excavation sites, number of backfill sites, number of designated borrow pits, number of designated disposal areas, units of soil transported from the cut site to the fill site, the actual share of costs that are affordable to the cut and fill sites, the units of soil transported from a borrow pit to the fill site, and the units of soil transported from the cut site to a disposal area are represented by separate variables.

3.2.2 Initial Population and Evaluation of Objective Functions

First, the number of generations, the population, and the variables are initialized. Each chromosome in the population is produced according to a random number generated by a Mersenne Twister algorithm. The numbers are then scaled to the range of the variable. Here, a random number r is generated for each individual in the population. If r is less than 0.5, then the value of the allele becomes 0; otherwise, the value of the allele becomes 1. Fitness values are computed according to the values of the genes for each chromosome.

3.2.3 Non-dominating Sorting

The generated population is sorted according to non-domination. Every chromosome is ranked in ascending order according to their fitness function values; the higher the rank, the lower the non-domination of the chromosomes. In general, chromosomes with a rank of 1 are non-dominated. Theoretically, the number of non-dominated chromosomes increases as the number of generations increases because the search space gets

wider and the likelihood of obtaining more potential chromosomes increases.

3.2.4 Measurement of Crowding Distance

Each chromosome in the sorted population is assigned to a crowding distance. The crowding distance is the relative density of an individual (chromosome) in a particular front in the population. Thus, crowding distances are assigned in a front-wise manner. Here, the crowding distance can be calculated according to Equation (11). The authors set n as the number of chromosomes in the i_{th} front F_i ; for each individual in front F_i , the distance is initialized to be zero for all individuals in $F_i(d(0))$. For each objective function m , individuals in F_i are sorted based on m and assigned a computed distance in n as a boundary value of the distance.

$$d = d(0) + \frac{m(j+1) - m(j-1)}{m_{max} - m_{min}} \quad (11)$$

In Equation (11), n , $m(j+1)$, $m(j-1)$, m_{max} , and m_{min} signify the number of chromosomes in the i_{th} front F_i , the objective function value of the $(j+1)$ -th individual, the objective function value of the $(j-1)$ -th individual, the maximum value of the objective function in the front, and the minimum value of the objective function in the front, respectively.

3.2.5 Tournament Selection

The authors set the size of the mating pool as z , and for each individual in z , n individuals in the population are randomly chosen. For each individual in n , the rank and crowding distance are collected, and the candidate with the lowest rank is found. If more than one individual has the lowest rank, the individual whose crowding distance is highest is selected and subsequently added to the mating pool.

3.2.6 Crossover and Mutation

The authors set the crossover probability to 0.9 and the mutation probability to 0.1. In general, the crossover procedure takes two chromosomes from the generated population and hybridizes them in order to generate new offspring that inherit the properties of their forbears. For each chromosome i in the mating pool, 2 individuals are randomly chosen and a random number r is generated for each gene g in the chromosome. If r is less than or equal to 0.5, $temp = (2 \times r)^{1/10}$; otherwise, $temp = (2 \times (1-r))^{1/10}$. The variance = $0.5 ((1 - temp) g (parent 1) (1 - temp) g (parent 2))$, and if the variance is less than 0.5, g becomes 0; otherwise, g becomes q . The value of g is scaled to the range of the variables. A mutation procedure is performed after the crossover operation. During this process, the value of a gene is randomly changed. Here, polynomial mutation is adopted as the mutation procedure. The value of genes from randomly selected parent chromosomes are changed within the range of respective variables, over which crossover and mutation policies are followed. The fitness function values for the offspring are computed and concatenated to the offspring population after the crossover and mutation procedures.

3.2.7 New Population Generation and Termination Condition

A new population is generated by replacing chromosomes in the original population. The individuals with higher ranks are chosen and then added to the population until the population size is reached. The last front is included in the population based on the crowding distance. The search process stops when the generation number reaches its maximum value.

3.3 Computational Results

The results of a numerical analysis, performed by applying the NSGA-II algorithm to the aforementioned multi-objective optimization problem are presented. The test platform is Matlab2011a. The variables X_j , Y_k , and Z_{jk} are binary with values of 0 or 1. All other variables have values within the ranges shown in Tables 2. and 3. One of optimized earthmoving schedule is presented in Table 4.

The authors have set the number of cut and fill sites as 3 and 7, respectively, and one-to-one relationships exist among sites.

Here, the population size and number of generations are unlimited, while the multiple objective functions are minimized. First, holding the population size at 200, the authors experiment with different numbers of generations. In this trial attempt, a minimum value is obtained at the 177th generation, where the number of non-dominated solutions is 191. The deviation in the result could be decreased by concentrating on a particular region as the number of generations is increased. At a population size of 300, one of the minimum values for the first objective function is obtained.

Table 2. Data Input (1/2)

$L_{CF_{jk}}$	Distance(km)	$L_{CF_{jk}}$	Distance(km)
$L_{CF_{11}}$	3.3	$L_{CF_{24}}$	7.2
$L_{CF_{12}}$	2.1	$L_{CF_{25}}$	2.2
$L_{CF_{13}}$	8.2	$L_{CF_{26}}$	8.9
$L_{CF_{14}}$	7.4	$L_{CF_{27}}$	7.8
$L_{CF_{15}}$	6.5	$L_{CF_{31}}$	3.1
$L_{CF_{16}}$	2.9	$L_{CF_{32}}$	6.9
$L_{CF_{17}}$	6.0	$L_{CF_{33}}$	2.0
$L_{CF_{21}}$	4.1	$L_{CF_{34}}$	13.4
$L_{CF_{22}}$	4.1	$L_{CF_{35}}$	6.3
$L_{CF_{23}}$	7.9	$L_{CF_{36}}$	6.7
		$L_{CF_{37}}$	12.8

Table 3. Data Input (2/2)

Site	$L_{CD_{jd}}$ $/L_{F_{B_{kb}}}$	EST	LST	$D_{C_j^i}$ $/D_{F_k^i}$	$\frac{\sum R_{C_j^i}}{\sum R_{F_k^i}}$	$\frac{\sum R_{C_j^i}}{D_{F_i}}$	$\frac{SR_{C_j^i}}{SR_{F_k^i}}$
C_1	8.4 km	6/8	6/15	32d	+6720	210	0.5
C_2	6.1 km	7/1	7/23	16d	+3072	192	0.7
C_3	7.7 km	7/9	7/14	15d	+2790	186	0.3
F_1	2.9 km	7/1	7/28	14d	-2346	168	0.9
F_2	2.1 km	6/21	7/8	14d	-1580	105	0.4
F_3	4.2 km	7/13	7/19	24d	-1935	84	0.6
F_4	7.3 km	6/7	6/19	32d	-4249	133	0.1
F_5	4.8 km	7/11	7/13	5d	-528	105	0.8
F_6	2 km	6/3	6/7	7d	-1317	36	0.7
F_7	1 km	7/9	7/13	11d	-564	51	0.9

The increase in the search space also increases the number of non-dominated solutions to 285, thereby yielding a better solution set. Minimum values for the second and third objective functions are attained at population sizes of 200 and 240, respectively. The value of the objective function tended to increase with

Table 4. Daily Earthmoving Schedule

C1				C2				C3				BP*	Revenue
Units	Share ratio	Units	Share ratio	Units	Share ratio	Units	Share ratio	Units	Share ratio	Units	Share ratio		
F1	$U_{CF_{11}}^i$ 42	$SR_{C_1^i}^{actl}/0.4$ $SR_{F_1^i}^{actl}/0.6$	$U_{CF_{21}}^i$ 54	$SR_{C_2^i}^{actl}/0.3$ $SR_{F_1^i}^{actl}/0.7$	$U_{CF_{31}}^i$ 62	$SR_{C_3^i}^{actl}/0.2$ $SR_{F_1^i}^{actl}/0.8$	$\sum I_{B_1^i}$ 10						\$26,754
F2	$U_{CF_{12}}^i$ 0	$SR_{C_1^i}^{actl}/0.0$ $SR_{F_2^i}^{actl}/0.0$	$U_{CF_{22}}^i$ 58	$SR_{C_2^i}^{actl}/0.6$ $SR_{F_2^i}^{actl}/0.3$	$U_{CF_{32}}^i$ 0	$SR_{C_3^i}^{actl}/0.0$ $SR_{F_2^i}^{actl}/0.0$	$\sum I_{B_2^i}$ 47						\$14,855
F3	$U_{CF_{13}}^i$ 71	$SR_{C_1^i}^{actl}/0.5$ $SR_{F_3^i}^{actl}/0.5$	$U_{CF_{23}}^i$ 11	$SR_{C_2^i}^{actl}/0.5$ $SR_{F_3^i}^{actl}/0.5$	$U_{CF_{33}}^i$ 0	$SR_{C_3^i}^{actl}/0.0$ $SR_{F_3^i}^{actl}/0.0$	$\sum I_{B_3^i}$ 2						\$48,346
F4	$U_{CF_{14}}^i$ 0	$SR_{C_1^i}^{actl}/0.0$ $SR_{F_4^i}^{actl}/0.0$	$U_{CF_{24}}^i$ 0	$SR_{C_2^i}^{actl}/0.0$ $SR_{F_4^i}^{actl}/0.0$	$U_{CF_{34}}^i$ 0	$SR_{C_3^i}^{actl}/0.0$ $SR_{F_4^i}^{actl}/0.0$	$\sum I_{B_4^i}$ 133						\$4,574
F5	$U_{CF_{15}}^i$ 68	$SR_{C_1^i}^{actl}/0.3$ $SR_{F_5^i}^{actl}/0.7$	$U_{CF_{25}}^i$ 21	$SR_{C_2^i}^{actl}/0.3$ $SR_{F_5^i}^{actl}/0.7$	$U_{CF_{35}}^i$ 14	$SR_{C_3^i}^{actl}/0.3$ $SR_{F_5^i}^{actl}/0.7$	$\sum I_{B_5^i}$ 2						\$33,925
F6	$U_{CF_{16}}^i$ 12	$SR_{C_1^i}^{actl}/0.4$ $SR_{F_6^i}^{actl}/0.6$	$U_{CF_{26}}^i$ 5	$SR_{C_2^i}^{actl}/0.5$ $SR_{F_6^i}^{actl}/0.5$	$U_{CF_{36}}^i$ 19	$SR_{C_3^i}^{actl}/0.3$ $SR_{F_6^i}^{actl}/0.7$	$\sum I_{B_6^i}$ 0						\$54,024
F7	$U_{CF_{17}}^i$ 8	$SR_{C_1^i}^{actl}/0.2$ $SR_{F_7^i}^{actl}/0.8$	$U_{CF_{27}}^i$ 31	$SR_{C_2^i}^{actl}/0.1$ $SR_{F_7^i}^{actl}/0.9$	$U_{CF_{37}}^i$ 10	$SR_{C_3^i}^{actl}/0.2$ $SR_{F_7^i}^{actl}/0.8$	$\sum I_{B_7^i}$ 2						\$23,793
DA*	$\sum I_{D_1^i}$ 9		$\sum I_{D_1^i}$ 12		$\sum I_{D_1^i}$ 81								
Revenue	\$37,834		\$24,748		\$7,345								

*DA: sum of soil disposed in the disposal area, BP: sum of soil procured from the borrow pit

a higher population size, meaning that a population size of 300 shows the most ideal result in this particular numerical experiment. The generation conducted with minimum fitness values for each population is affected by the increase in the population size. With a population size of 300, the authors also could observe a minimum value at generation 164.

4. Summary and Conclusions

In this research, the authors presented an inter-site earthmoving optimization strategy to reuse uncontaminated excess soil by means of a solution that prevents conflicting objectives while simultaneously satisfying earthwork schedules. An approach for practical inter-site soil transactions is required, given that the reuse of uncontaminated excess soil brings diverse benefits, i.e., earthmoving costs savings and the lessening of environmental burdens. In an attempt to activate soil transactions, the authors recognized the need to minimize the earthmoving costs of both parties, as the minimization of one side's earthmoving cost could affect the costs incurred by the other side, thereby hindering the adoption of inter-site earthmoving operations. An MOEA algorithm, known as NSGA-II, is adopted to achieve the aforementioned goals in this research. Consequently, an optimized outcome in terms of costs and schedules is provided and it capably copes with the various constraints given construction site information. In contrast to manual earthmoving scheduling, which is cumbersome even to responsible field managers, the effectiveness of the devised approach is demonstrated, as it presents the maximized amount of soil recycling.

Inter-site earthmoving optimization would be facilitated in real world situations when it is possible to incorporate existing objectives and all their associated uncertainties. For further research, other objectives and uncertainties need to be considered to develop a practical optimization model that encompasses a wide variety of earthmoving factors and complex transaction options.

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